Renewable and Sustainable Energy Reviews 29 (2014) 911–923

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Mixed integer programming of multi-objective security-constrained hydro/thermal unit commitment

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ARTICLE INFO

Article history:
Received 5 June 2013
Received in revised form
1 September 2013
Accepted 8 September 2013
Available online 8 October 2013

Keywords:
Security-constrained unit commitment
Mixed integer linear programming
Multi-objective optimization
Augmented ε-constraint method
Hydro units

ABSTRACT

This paper proposes a method for short term security-constrained unit commitment (SCUC) for hydro and thermal generation units. The SCUC problem is modeled as a multi-objective problem to concurrently minimize the ISO's cost as well as minimizing the emissions caused by thermal units. The non-linearity of valve loading effects is linearized in the presented problem. In order to model the SCUC problem more realistically, this paper considers the dynamic ramp rate of thermal units instead of the fixed rate. Moreover, multi-performance curves pertaining to hydro units are developed and the proposed SCUC problem includes the prohibited operating zones (POZs). Besides, the model of SCUC is transformed into mixed integer linear programming (MILP) instead of using mixed integer non-linear programming (MINLP) which has the capability to be solved efficiently using optimization software even for real size power systems. Pareto optimal solutions are generated by employing lexicographic optimization as well as hybrid augmented-weighted ε-constraint technique. Furthermore, a Fuzzy decision maker is utilized in this paper to determine the most preferred solution among Pareto optimal solutions derived through solving the proposed multi-objective SCUC problem. Eventually, the proposed model is implemented on modified IEEE 118-bus system comprising 54 thermal units and 8 hydro units. The simulation results reveal that the solutions obtained from the proposed technique in comparison with other methods established recently are superior in terms of total cost and emission output.

Contents

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1364-0321/$ - see front matter
http://dx.doi.org/10.1016/j.rser.2013.09.020

1. Introduction

In vertically integrated power systems, the goal of implementing unit commitment (UC) is optimizing energy sources in a way that the load demand is supplied with the least cost. Besides, if security criteria are included in the UC, then it is known as security-constrained unit commitment (SCUC). If the UC is performed by each of the generation companies (GENCOs) to optimize energy sources in a way that the GENCO's profit becomes maximized, it is called Price-Based Unit Commitment (PBUC) [1]. A MILP framework for the UC problem relating to thermal units is proposed in Ref. [2] in which fewer number of binary variables and constraints are needed compared to the models reviewed before leading to remarkable less computational burden. On the basis of the SCUC model presented in Ref. [3], an efficient AC corrective/preventive contingency dispatch comprising 24-h time period is proposed. A SCUC model considering energy and ancillary services auction is proposed in Ref. [4] which is applicable to reserve requirements optimization in electricity market framework by ISO. Ref. [5] has suggested a model having the capability to solve the coordinated generation and transmission maintenance scheduling with SCUC in which the scheduling period is weeks to months and decomposition of the optimization problem is performed using Lagrangian relaxation method. In Ref. [6], the intermittent and volatile wind power generation is included in the SCUC problem while Benders decomposition is employed to solve the problem. The problem of determining optimal response of a thermal unit along with a hydro GENCO to a spot electricity market is investigated in Refs. [7,8] in which the profit of the unit through participating in spot market to sell both energy and spinning reserve is set as the objective function to be maximized. The problem of short- hydrothermal scheduling is addressed in Ref. [9] utilizing Modified Differential Evolution (MDE) algorithm. Ref. [10] has proposed mid-term risk-constrained hydro-thermal scheduling problem in a stochastic framework for a GENCO that its objective is assigned to maximize payoffs as well as minimizing financial risks during its mid-term scheduling of thermal, cascaded hydro in addition to pumped-storage units. The act of determining the PBUC status for power generation companies is performed in Ref. [10] through solving self-scheduling problem prior to giving their bids to a day-ahead market. The proposed model is formulated as a deterministic optimization problem to maximize the profit exploiting 0/1 MILP technique. Ref. [11] has employed Improved Particle Swarm Optimization (IPSO) algorithm to solve the short-term hydrothermal scheduling problem in order to obtain the optimal power generation. The GENCO's arbitrage problem is taken into consideration in Ref. [12] utilizing stochastic PBUC while modeling the associated risks. The requirements of short term hydro-thermal scheduling (SHTS) problem are not met anymore after passage of the clean air act amendments in 1990 [13] and the emission issues must be unavoidably taken into account. Ref. [14] was one of the foremost work trying to solve the UC problem while emissions minimization had been taken into consideration as another objective function and the proposed problem was solved employing weighting method to make the two-objective problem a single-objective optimization problem. Unsupported efficient solutions cannot be generated by weighting method in multi-objective integer problems as well as MIP ones. The results derived from weighting method are highly dependent on the scaling of objective functions. Thus, objective functions should be scaled to a common scale prior to the weighted sum formation [15]. Multi-objective evolutionary algorithm is applied to the environmental/economic dispatch (EED) problem in Ref. [16] to simultaneously minimize the fuel cost as well as minimizing the emissions. Unlike weighting method needing large number of optimization problems to be solved, the suggested approach in Ref. [16] requires only a single run to trace the Pareto optimal front. Ref. [17] solves the stochastic multi-objective generation scheduling problem employing weight age pattern search methods while operating cost, NO_x and the risk caused by the variance of active as well as reactive power mismatch are set to be minimized concurrently and the proposed model is implemented on IEEE 11-bus system. The problem of minimizing cost, SO_2, CO_2, and NO_x is addressed in Ref. [18] using Non-Inferior Surface estimation method. The electric power dispatch is done in Ref. [19] employing a fuzzified multi-objective particle swarm optimization (MOPSO) algorithm while economic and environmental issues are all taken into consideration and the results derived from this technique is compared with those obtained from weighted sum method and evolutionary multi-objective optimization algorithms. Ref. [20] presents an interactive Fuzzy satisfying approach on the basis of evolutionary programming (EP) technique while the decision maker (DM) is supposed to have Fuzzy targets for each objective function; afterwards the corresponding Pareto optimal solution for the decision maker targets is generated by implementing the Fuzzy satisfying method based on the EP technique. A stochastic multi-objective framework is presented in Ref. [21] utilizing Fuzzy decision making wherein the tradeoff relation between conflicting objective functions is simulated by weighting method. ε-constraint is another multi-objective technique utilized in Ref. [22] to produce non-dominated solutions for thermal power dispatch with operating cost and emissions as objective functions that are assumed to be minimized; After that, the most preferred solution is determined for the proposed multi-objective problem by surrogate worth trade-off approach. In Refs. [23,24], the economic/emission load dispatch problem is formulated in the multi-objective framework and solved employing Hopfield neural networks and non-dominated sorting genetic algorithm (NSGA), respectively. Ref. [25] suggests MOPSO algorithm to solve the stochastic economic/emission load dispatch problem. The NSGA is utilized in Ref. [26] to generate the Pareto optimal front and the most compromise solution is selected by multi-attribute decision making method. The ε-constraint is applied to the multi-objective problem with objective functions of GENCO's profit to be minimized and emissions to be minimized in a day-ahead joint

Nomenclature

Indices

I	index for thermal units
j	index for hydro units
t	index for time interval (h)

Constants

η	conversion factor equal to 3.6×10^{-3} (hm^3/s/m^3/h)
Θ	time intervals of the considered planning horizon
$\underline{\theta}(j,t)$	minimum water discharge of hydro unit j at time t (m^3/s)
$\overline{\theta}(j,t)$	maximum water discharge of hydro unit j at time t (m^3/s)
τ_{ij}	time delay of water transport between hydro unit i reservoir and hydro unit j reservoir (h)
A_i	shut-down cost of thermal unit i ($)
A_j	start-up cost of hydro unit j ($)
$b_n(i)$	slope of block n of fuel cost curve pertaining to thermal unit i ($/MW h)
$b_n(j)$	slope of the volume block n of the reservoir pertaining to hydro unit j (m^3/s/hm^3) (1 hm^3 = 10^6 m^3)
$b_n^k(j)$	slope of the block n pertaining to the performance curve k of hydro unit j (MW/m^3/s)
$be_n(i)$	slope of segment n in emission curve of thermal unit i (lbs/MW h)
e_i	valve loading coefficient
$e_{\min}(i)$	minimum emission generation of thermal unit i (lbs)
$E(p_{n-1}^u(i))$	emission generation of $n-1$th upper limit in emission curve of thermal unit i (lbs)
f_i	valve loading coefficient
$F(p_{n-1}^u(i))$	cost of generation of $n-1$th upper limit in fuel cost curve pertaining to the thermal unit i($/h)
$F(j,t)$	forecasted natural water inflow of the reservoir associated to the hydro unit j at hour t (hm^3/h)
L	number of variable head
M	number of prohibited operating zones
NL	number of piecewise linearization blocks pertaining to the variable cost function
$p_{min}(i)$	minimum output power of thermal unit i (MW)
$p_{max}(i)$	maximum output power of thermal unit i (MW)
$\underline{p}_n(j)$	minimum output power of hydro unit j for performance curve n (MW)
$\overline{p}(j)$	capacity of hydro unit j (MW)
$p_n^d(i)$	lower limit of nth prohibited operating zone pertaining to thermal unit i (MW)
$p_{n-1}^u(i)$	upper limit of $n-1$th prohibited operating zone pertaining to thermal unit i (MW)
$\underline{Q}(j)$	minimum water discharge of hydro unit j provided that it is on (m^3/s)
$\overline{Q}_n(j)$	maximum water discharge of block n of hydro unit j (m^3/s)
$RDL_n(i)$	ramp-down limit for block n (MW)
$RUL_n(i)$	ramp-up limit for block n (MW)
$SUE(i)$	emission generated by thermal unit i when started-up (lbs)
$SDE(i)$	emission generated by thermal unit i when shut-down (lbs)
$SD(i)$	shut-down ramp rate limit of thermal unit i (MW h)
$SU(i)$	start-up ramp rate limit of thermal unit i (MW h)
$v_0(j)$	minimum volume water of the reservoir pertaining to hydro unit j (hm^3)
$v^0(j)$	volume of the reservoir at the beginning of the planning horizon (hm^3)
$v^{\Theta}(j)$	volume of the reservoir at the end of the planning horizon (hm^3)
$v_n(j)$	maximum volume of the reservoir j pertaining to the nth variable head (hm^3)

Variables

$\beta_n(i,t)$	binary variable that is equal to 1 if block n of fuel cost curve of thermal unit i at time t is selected
$\beta_n(j,t)$	binary variable that is equal to 1 provided that the variable head $n+1$ of hydro unit j at time t is selected
$\chi_n(i,t)$	binary variable that is equal to 1 provided that the output power of thermal unit i at time t has overstepped block n of valve loading effects curve
$\delta_n(i,t)$	generation of block n of fuel cost curve of thermal unit i at time t (MW)
Φ	payoff table
$\psi_n(i,t)$	generation of block n pertaining to the thermal unit i at time t of valve loading effects curve (MW)
$\psi_n(j,t)$	volume of block n for the reservoir of hydro unit j at time t (hm^3)
Ω	feasible region
μ^r	total membership function of the rth Pareto optimal solution
μ_n^r	degree of optimality for the nth objective function in the rth Pareto optimal solution
$B(i,t)$	start-up cost of thermal unit i at time t ($)
$C(i,t)$	cost of valve loading effects pertaining to the thermal unit i at time t ($)
$F(i,t)$	fuel cost of thermal unit i at time t ($)
F^{COST}	main objective function
$F^{EMISSION}$	second objective function
$h_n(j,t)$	binary variable that is equal to 1 provided that the water discharge of hydro unit j at time t has overstepped block n
$I(i,t)$	binary variable that is equal to 1 provided that the thermal unit i is on-line at time t
$I(j,t)$	binary variable that is equal to 1 provided that the hydro unit j is on-line at time t
$I_d(i,t)$	binary variable that is equal to 1 if the thermal unit i at time t provides non-spinning reserve when unit is off
$P(i,t)$	output power of thermal unit i at time t (MW)
$\overline{p}(i,t)$	maximum output power of thermal unit i at time t (MW)
$p(j,t)$	output power of hydro unit j at time t (MW)
$Q(j,t)$	water discharge of hydro unit j at time t (m^3/s)
$q_n(j,t)$	water discharge of block n pertaining to hydro unit j at time t (m^3/s)
$RDL(p(i,t))$	ramping-down limit of thermal unit i at time t (MW)
$RUL(p(i,t))$	ramping-up limit of thermal unit i at time t (MW)
$s(j,t)$	spillage of the reservoir associated to hydro unit j at hour t (m^3/s)
$v(j,t)$	amount of water pertaining to hydro unit j reservoir at hour t (hm^3)
$y(i,t)$	binary variable that is equal to 1 provided that thermal unit i is started-up at the beginning of time t
$y(j,t)$	binary variable that is equal to 1 provided that hydro unit j is started-up at the beginning of time t
$z(i,t)$	binary variable that is equal to 1 provided that thermal unit i is shut-down at the beginning of time t
$z(j,t)$	binary variable that is equal to 1 provided that hydro unit j is shut-down at the beginning of time t

Sets

I	set of thermal generating units
J	set of hydro generating units
N	set of indices of blocks of the piecewise linearization of hydro units' performance curve
NE	set of indices of blocks of the piecewise linearization of thermal units' emission curve
T	set of indices of periods of the market time horizon
Ω_j	set of upstream reservoirs of hydro unit j

reserve and energy market. The problem of short-term multi-objective hydrothermal scheduling taking into consideration the cost and emissions as two objective functions is solved using in Refs. [29–31] using differential evolution, quantum-behaved particle swarm optimization, and quantum-behaved particle swarm optimization techniques, respectively while ignoring security issues as well as implementing the model on a case study with small size. Further information on optimization techniques presented to solve the SHTS problem can be found in Refs. [32,33].

This paper solves the multi-objective problem with total cost and emission as objective functions that are intended to be minimized employing lexicographic optimization and augmented ε-constraint technique. This approach can be well implemented by the ISO for scheduling wherein more practical constraints of thermal and hydro units are considered in comparison with previous works in this area. So far, there is not any work devoted to solve the SCUC problem minimizing total cost as well as minimizing emissions for a large-scale case study (IEEE 118-bus system) taking into consideration high number of practical limitations, such as Prohibited Operation Zones (POZs), variable start-up cost function, minimum up-time (MUT) and minimum down-time (MDT), valve loading effects, dynamic ramp-up limit (RUL) and ramp-down limit (RDL) for thermal units as well as multi-performance curves for hydro units. The main contributions of this paper are listed below:

- Proposing a multi-objective framework for the SCUC problem taking cost and emissions as the two objective functions.
- Employing lexicographic optimization along with augmented ε-constraint method to simultaneously minimize the total cost and emissions of thermal generating units.
- Presenting valve loading effect with linear formulation as well as replacing fixed ramp rate limit with dynamic one for thermal units.
- Using flexible approach for multi POZs of thermal generating units as well as multi-performance curves for hydro units.
- Linearizing the MINLP problem and converting it to MILP problem and using an effective analytical technique to solve the proposed problem.

The remainder of this paper is categorized as below:

The proposed lexicographic optimization and augmented ε-constraint method are included in Section 2. The thermal and hydro model is presented in Section 3 while Section 4 comprises the case studies and represents the results with detailed discussion. Finally, some relevant conclusions of this paper are drawn in Section 5.

2. Multi-objective mathematical programming

The concept of multi-objective mathematical programming (MMP) involves with more than one objective function and there is no longer a single optimal solution that concurrently optimizes all objective functions. In such situations, the most desired solution is intended to be derived by the DM. Also, the concept of optimality is substituted with efficiency or Pareto optimality i.e. the solution that cannot get better except making its performance worse in at least one of the other objective functions. An effective approach presented to deal with multi-objective problems is ε-constraint technique having one main objective function selected among all objective functions. The ε-constraint method is prior to traditional weighting methods from several aspects. The deficiency by the weighting methods is forming a single objective function out of multi-objective problem by uniting the objective functions using weighted sum. The advantages of utilizing ε-constraint can be listed as below [15,27,34]:

- The weighting method results in merely efficient extreme solutions for linear problems whereas non-extreme solutions can be generated through applying ε-constraint approach.
- Unlike the weighting method, in multi-objective integer programming problems as well as MIP ones, unsupported efficient solutions can be generated by ε-constraint.
- The weighting method highly depends on the scaling of objective functions while this issue is not important in the ε-constraint.
- The controlled number of efficient solutions can be generated in ε-constraint technique by effectively tuning the number of grid points in the range of each objective function.

In spite of the advantages of ε-constraint approach have, there are two key points that should be noted. First, there is no guarantee that the range of the objective functions over the efficient set is optimal while lexicographic optimization method is employed to overcome this deficit. The second problem with ε-constraint is the possibility of being dominated or inefficient of the produced Pareto optimal solutions. One likely way to eliminate this shortfall is to use augmented ε-constraint method. Further details on employing lexicographic optimization and augmented ε-constraint can be found in the previous paper of the authors in this area [34] while this procedure is not repeated in this paper. The importance of the objective functions is not taken into consideration by the augmented ε-constraint method during Pareto solutions generation. On the contrary, the augmented-weighted ε-constraint method clearly considers the relative importance of the objective functions in the Pareto solutions generation. In this paper, the MMP model of SCUC comprising two objective functions i.e. F_1, F_2 is solved using lexicographic optimization and hybrid augmented-weighted ε-constraint method. The detailed description of the MMP solution methodology is given in the next section.

2.1. Solution methodology of MMP

The MMP formulation on the basis of the augmented ε-constraint method is presented as (1) while Refs. [27,34] include further details:

$$\text{Min / Max}\left[F_1(x)+dir_1\, r_1 \sum_{i=2}^{p}\frac{s_i}{r_i}\right]$$
$$s.t.\ F_i(x)-dir_i s_i = e_i\ \forall\ s_i \in R^+,\ i=2,3,\dots,p. \tag{1}$$

where, the number of objective functions is denoted by p. dir_i expresses the direction of the ith objective function that in the case of minimizing the objective function, dir_i is -1 while $+1$ shows that the objective function is supposed to be maximized. The efficient solutions of the problem are derived by parametrical iterative variations in e_i. The introduced slack or surplus variables for the MMP problem's constraints is denoted by s_i. Moreover, the second term of the MMP problem comprises $r_1(s_i/r_i)$ to prevent any scaling problem. Because of the augmentation of the objective function F_1 by the second term, formulation (1) is called augmented ε-constraint approach. The generation of only efficient solutions by the augmented ε-constraint can be expressed [34] while it is proven in Ref. [15]. The ranges of objective functions should be determined to implement the ε-constraint approach. These ranges can be computed from payoff table as the most usual way. The ordinary approach to form the payoff table does not ensure that the solutions derived from individual optimization of the objective functions are efficient solutions or Pareto optima. Hence, lexicographic optimization is exploited in this paper to eliminate the defect by inefficient solutions once the payoff table is formed. In general, the procedure of lexicographic optimization of several objective functions is to take and optimize the first objective function while between possible alternative optima optimize for the second objective function and so on. Ref. [34] includes the detailed procedure of calculating payoff table for the MMP problem. The Payoff table is a p by p table. The obtained values of the objective function F_i are included in the ith column of the payoff table wherein range of the objective function F_i is determined by the minimum and the maximum values for the ε-constraint technique. So, the range of each objective function is determined as Eq. (2):

$$r_i = F_i^{\mathrm{Max}} - F_i^{\mathrm{Min}} \tag{2}$$

The next step after determining the range (r_i) pertaining to all objective functions from payoff table is to divide the range of the remaining objective functions $F_2,\ldots, F_p$ to $n_2,\ldots, n_p$ into same intervals utilizing $(n_2-1),\ldots, (n_p-1)$ intermediate grid points with equal distances, respectively. The total grid points with consideration of the minimum and the maximum values of the range would be $(n_2+1),\ldots, (n_p+1)$ corresponding to $F_2,\ldots, F_p$, respectively. Therefore, the Pareto optimal solution is derived through solving $(n_2+1)\times(n_3+1)\times\ldots\times(n_p+1)$ optimization sub-problems. The importance of objective functions is excluded by the augmented ε-constraint technique once the Pareto solutions are generated which is incompatible with the DM purposes. However, augmented-weighted ε-constraint technique is used in this paper so that the relative significance of the objective functions is clearly modeled in the Pareto solutions generation. In this regard, the objective function in (1) is changed as below according to the augmented-weighted ε-constraint technique:

$$\mathrm{Min}\ /\ \mathrm{Max}\left[w_1 F_1(x) + dir_1\ r_1 \sum_{i=2}^{p} \frac{w_i s_i}{r_i}\right]$$
$$s.t.\ F_i(x) - dir_i\ s_i = e_i\ \forall\ s_i \in R^+,\ i = 2, 3, \ldots, p. \tag{3}$$

where, the weighting factors of DM for the ith objective function are denoted by w_i. Note that, the technique presented here as augmented-weighted ε-constraint is quite different from the procedure of

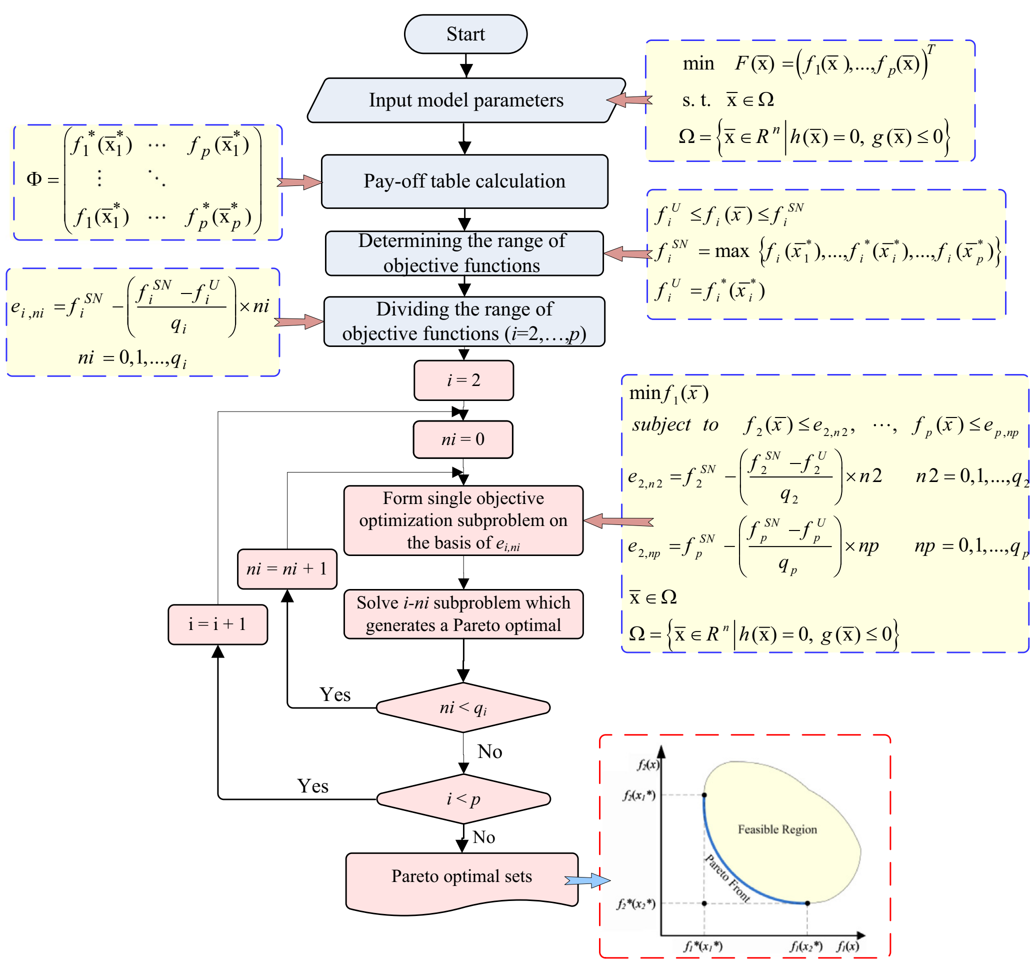

Fig. 1. Flowchart of the ε-constraint optimization method for the MMP problem.

weighting method that results in a single solution for a set of weights without ensuring the efficiency of the solution. The proposed mathematical formulation in (4) must be solved to generate Pareto optimal solution in each sub-problem.

$$Min/Max\left[F_1(x)+\left(\frac{dir_1\ r_1}{w_1}\right)\sum_{i=2}^{p}\frac{w_i s_i^k}{r_i}\right]$$
$$s.t.\ F_i(x)-dir_i\ s_i^k=e_i^k\ \forall\ s_i\in R^+,\ i=2,3,...,p,k=0,1,...,q_i \tag{4}$$

$$e_i^k=F_i^{Min}\frac{(dir_i+1)}{2}-F_i^{Max}\frac{(dir_i-1)}{2}+\frac{(dir_i\ r_i\ k)}{q_i}$$
$$\forall\ i=2,3,...,p,k=0,1,...,q_i \tag{5}$$

2.2. Fuzzy decision maker

A Fuzzy decision making technique is used in this paper as Refs. [34,35] after deriving the Pareto-optimal solutions through solving the optimization sub-problems to select the most preferred solution in accord with particular purpose of the application. In this technique, for each objective function of the MMP problem, a linear membership function is defined. Eq. (6) is defined as below for objective functions that are set to be minimized:

$$\mu_i^r=\begin{cases}1 & f_i^r\le f_i^{\min}\\ \frac{f_i^{\max}-f_i^r}{f_i^{\max}-f_i^{\min}} & f_i^{\min}\le f_i^r\le f_i^{\max}\\ 0 & f_i^r\ge f_i^{\max}\end{cases} \tag{6}$$

And for the objective function intended to be maximized, the linear membership function is defined in (7), as well.

$$\mu_i^r=\begin{cases}0 & f_i^r\le f_i^{\min}\\ \frac{f_i^r-f_i^{\min}}{f_i^{\max}-f_i^{\min}} & f_i^{\min}\le f_i^r\le f_i^{\max}\\ 1 & f_i^r\ge f_i^{\max}\end{cases} \tag{7}$$

where, the range of objective function f_i derived from payoff table is denoted by $f_i^{\min}$ and $f_i^{\max}$. The value of the ith objective function in the rth Pareto optimal solution as well as corresponding membership function are indicated by f_i^r and μ_i^r, respectively. The concept pursued by the value of obtained membership function μ_i^r is the nicety of the solution derived for the ith objective function in the rth Pareto optimal solution. Besides, for the rth Pareto optimal solution, the total membership function (μ^r) is defined on the basis of its individual membership functions as (8):

$$\mu^r=\frac{\sum_{i=1}^{p}w_i\mu_i^r}{\sum_{i=1}^{p}w_i} \tag{8}$$

where, ith objective function's weighting in the MMP problem is denoted by w_i and the p indicates the number of objective functions. By considering the significance of economic and security aspects, the system operator can choose the weighting value w_i. The best Pareto optimal solution of the MMP problem is the one with the highest value of membership function μ^r with respect to the assigned weight factors.

The presented MMP solution method is formed by coming together the augmented-weighted ε-constraint technique and lexicographic optimization. The procedure of the proposed method can be stated as follows:

Step 1: By employing the lexicographic optimization approach, the payoff table pertaining to a MMP problem is computed.
Step 2: The range of the ith objective function (i=2, 3,…, p) is determined using payoff table as Eq. (2).
Step 3: According to the formulation proposed in (5), the range of at least p-1 objective functions is divided into q_i (i=2, 3,…, p) equal intervals.
Step 4: The feasible optimization sub-problems in (4) are solved applying the presented MMP solution method to produce the Pareto efficient solution while the infeasible ones are discarded.
Step 5: The efficient solutions derived from step 4 are evaluated using the Fuzzy decision making process (6)–(8) to choose the most desired Pareto optimal solution.
The solution method on the basis of ε-constraint optimization technique for the proposed MMP problem is depicted in Fig. 1 as a flowchart.

3. MIP formulation for SCUC

The two objective functions of the presented framework for the SCUC problem can be stated as (9):

$$\text{MultiObjective function}=\begin{cases}F_1 & \cos\ t\ \min\text{imization}\\ F_2 & \text{emmision}\ \min\text{imization}\end{cases} \tag{9}$$

where, the detailed description of the objective functions F_1, and F_2 pertaining to the SCUC problem is given in the following section.

3.1. Cost minimization

Minimizing cost is the main objective function in the proposed SCUC problem as (10):

$$F_1:Min\ F^{COST}=\sum_{t\in T}\left(\sum_{j\in J}A_jy(j,t)+\sum_{i\in I}A_iZ(i,t)+B(i,t)+F(i,t)+C(i,t)\right) \tag{10}$$

where, the total cost is denoted by F^{COST} including thermal and hydro units operation cost that it is intended to be minimized by ISO. The start-up cost is indicated by the first term [8,36] while thermal unit's cost comprising fuel cost, valve loading effects cost, shut-down cost and start-up cost will be explained in detail later. Because of wear and tear of the windings and mechanical equipment as well as loss of water during start-up and maintenance in addition to malfunctions in the control system, start-up cost of hydro units is considered by authors in Ref. [36].

3.2. Emission minimization

$$F_2:\ Min\ F^{EMISSION}=\sum_{i\in EMG}\sum_{t\in T}\left\{\begin{array}{l}e_{\min}(i)I_d(i,t)+SUE(i)y(i,t)+SDE(i)z(i,t)\\+\sum_{n=1}^{NE}[\beta_n(i,t)E(p_{n-1}^u(i))+be_n(i)\ \delta_n(i,t)]\end{array}\right\} \tag{11}$$

where, the first term indicates the emission caused by thermal units which are off and provide non-spinning reserve [37] and $EMG=\{SO_2, NO_x\}$ as the most significant emissions caused by electricity generation section affecting the environment are SO_2 and NO_x [28,38]. Authors of Ref. [28] have modeled the emissions as a quadratic term while the linearized form using piecewise linear approximation is illustrated in Fig. 2. It should be noted that, in order to more precise modeling, emission caused by the start-up and shut-down of thermal units is included in the emission function.

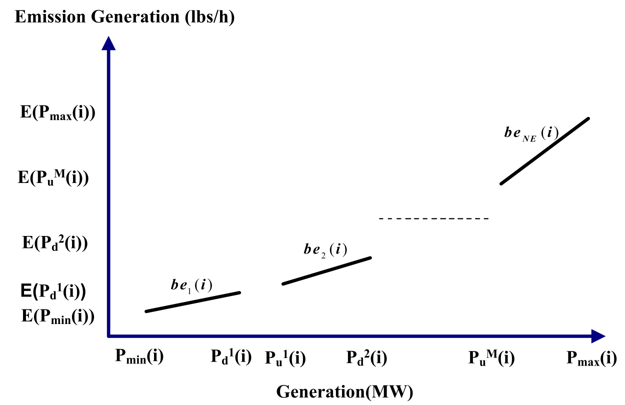

Fig. 2. Piecewise linear emission generation curve with M prohibited zones.

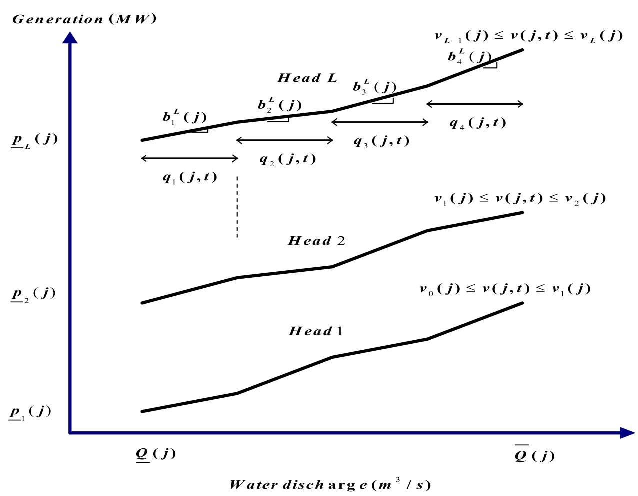

Fig. 3. Piecewise linear non-concave unit performance curve for hydro unit j at hour t.

3.3. Hydro units' model

The relationship between water discharge, generated power and multi-head of reservoir is depicted in Fig. 3 where the connection of hydro units is both parallel and in series. Multi-head reservoir is used due to the small storage capacity of reservoirs and also because the generated power depends on the hydro unit head. The number of heads is shown with L in the following formulations while the higher number of L improves the model accuracy.

3.3.1. Linear formulations for volume and multi-head

This section comprises the linear formulations of hydro power units with L heads (Fig. 3):

$$\beta_1(j,t) \geq \beta_2(j,t) \geq \beta_3(j,t) \geq \cdots \forall j \in J, \forall t \in T \tag{12}$$

$$v(j,t) \leq v_L(j)\beta_{L-1}(j,t) + \sum_{n=2}^{L} v_{n-1}(j)[\beta_{n-2}(j,t) - \beta_{n-1}(j,t)] \quad \forall j \in J, \forall t \in T \tag{13}$$

$$v(j,t) \geq v_{L-1}(j)\beta_{L-1}(j,t) + \sum_{n=3}^{L} v_{n-2}(j)[\beta_{n-2}(j,t) - \beta_{n-1}(j,t)] \quad \forall j \in J, \forall t \in T \tag{14}$$

$$v(j,t) \geq v_0(j) \qquad \forall j \in J, \forall t \in T \tag{15}$$

where,

$\beta_0(j,t) = 1.$

when $n+1$th is used, binary variable $\beta_n(j,t)$ would be equal to 1. Constraint (12) eliminates the 0–1 conflicts between these binary variables. Right head corresponding to volume value is indicated by constraints (13)–(15). Constraints (13)–(15) ensure that the volume value of each hydro unit at each time is greater than the minimum content of that hydro unit.

3.3.2. Linear power-discharge curve

The linear relationship between discharged water, generated power as well as variable head is declared as below:

$$p(j,t) - \underline{p}_k(j)I(j,t) - \sum_{n \in N} q_n(j,t)b_n^k(j) - \overline{p}(j)[(k-1) - \sum_{n=1}^{k-1} \beta_n(j,t) + \sum_{n=k}^{L-1} \beta_n(j,t)] \leq 0 \ \forall j \in J, \forall t \in T, 1 \leq k \leq L \tag{16}$$

$$p(j,t) - \underline{p}_k(j)I(j,t) - \sum_{n \in N} q_n(j,t)\, b_n^k(j) + \overline{p}(j)[(k-1) - \sum_{n=1}^{k-1} \beta_n(j,t) + \sum_{n=k}^{L-1} \beta_n(j,t)] \geq 0 \ \forall j \in J, \forall t \in T, 1 \leq k \leq L \tag{17}$$

The power generated by hydro unit j at time t and the minimum power generation of head k are denoted by $P(j,t)$ and $\underline{p}_k(j)$, respectively. $\beta_n(j,t)$ indicates the proper head and $\overline{p}(j)$ is the capacity of hydro unit j. $q_n(j,t)$ denotes the discharge of block n while the slope of the block n pertaining to the performance curve k of hydro unit j is represented by $b_n^k(j)$.

3.3.3. Water discharge limits

$$Q(j,t) = \underline{Q}(j)I(j,t) + \sum_{n \in N} q_n(j,t) \qquad \forall j \in J, \forall t \in T \tag{18}$$

$$\underline{\theta}(j,t) \leq Q(j,t) + s(j,t) \leq \overline{\theta}(j,t) \qquad \forall j \in J, \forall t \in T \tag{19}$$

where, water discharge of hydro unit j at time t is indicated by $Q(j,t)$ and equals to the minimum water discharge provided that the hydro unit is on, plus the water discharge of blocks. However, in order to meet flood and irrigation necessities, water discharge must be limited.

$$s(j,t) = \sum_{n=1}^{L} b_n(j)\psi_n(j,t) \qquad \forall j \in J, \forall t \in T \tag{20}$$

$$v(j,t) = v_0(j) + \sum_{n=1}^{L} \psi_n(j,t) \qquad \forall j \in J, \forall t \in T \tag{21}$$

$$[v_1(j) - v_0(j)]\beta_1(j,t) \leq \psi_1(j,t) \leq v_1(j) - v_0(j) \qquad \forall j \in J, \forall t \in T \tag{22}$$

$$[v_n(j) - v_{n-1}(j)]\beta_n(j,t) \leq \psi_n(j,t) \quad n = 2,3,....,L, \forall j \in J, \forall t \in T \tag{23}$$

$$\psi_n(j,t) \leq [v_n(j) - v_{n-1}(j)]\beta_{n-1}(j,t) \ n = 2,3,....,L, \forall j \in J, \forall t \in T \tag{24}$$

The reservoir spillage is modeled as a function of reservoir volume value. The slope of the block n pertaining to the reservoir volume value is denoted by $b_n(j)$ and block n of the reservoir volume value is denoted by $\psi_n(j,t)$. Constraint (21) indicates the relationship between reservoir content and the volume blocks. The first block of the reservoir volume is restricted by constraint (22) while other reservoir volume blocks at each time are restricted through constraints (26)–(28).

$$q_1(j,t) \leq \overline{Q}_1(j)I(j,t) \quad \forall j \in J, \forall t \in T \tag{25}$$

$$q_1(j,t) \ge \overline{Q}_1(j)h_1(j,t) \quad \forall j \in J, \forall t \in T \tag{26}$$

$$q_n(j,t) \le \overline{Q}_n(j)h_{n-1}(j,t) \quad \forall j \in J, \forall t \in T, \forall n \in N \tag{27}$$

$$q_n(j,t) \ge \overline{Q}_n(j)h_n(j,t) \quad \forall j \in J, \forall t \in T, \forall n \in N \tag{28}$$

$\overline{Q}_n(j)$ indicates the maximum water discharge of the nth block pertaining to hydro unit j and the binary variable $h_n(j,t)$ is equal to 1 if the water discharge of hydro unit j at time t has overstepped the nth block. Constraints (25) and (26) restrict the water discharge of the first block while other blocks of water discharge are restricted through constraints (27) and (28).

3.3.4. Initial and final volume

$$v(j,0) = v^0(j) \qquad \forall j \in J \tag{29}$$

$$v(j,\Theta) = v^\Theta(j) \qquad \forall j \in J \tag{30}$$

The initial and the final volume of the reservoir at the beginning and the end of the planning horizon are limited through constraints (29) and (30).

3.3.5. Water balance

In the cascaded configuration of hydro units, the water discharged from the upstream hydro unit is the inflow of the next downstream hydro unit. In Eq. (31) which indicates the continuity equation, the forecasted natural water inflow to the reservoir of the hydro unit j at time t is indicated by $F(j,t)$ and η denotes the conversion factor which is utilized to convert water discharge reservoir into stored water. Ω_j denotes the upstream reservoirs of hydro unit j and the time delay corresponding to the water transport from hydro units i to j is expressed by τ_{ij}.

$$\begin{aligned} v(j,t) = {} & v(j,t-1) + F(j,t) - \eta.(Q(j,t)+s(j,t)) \\ & + \eta \sum_{i \in \Omega_j} [Q(j,t-\tau_{ij}) + s(j,t-\tau_{ij})] \ \forall j \in J, \forall t \in T \end{aligned} \tag{31}$$

3.3.6. Operating services

Since, the hydro units are known as fast response units, they would be suitable to provide spinning reserve as well as non-spinning reserve. This paper uses formulations proposed in Refs. [37,39] as below:

$$p\,(j,t) + R(j,t) + N_u(j,t) \le \overline{p}\,(j)\,I(j,t) \quad \forall j \in J, \forall t \in T \tag{32}$$

$$N_d(j,t) \le QSC(j)(1 - I(j,t)) \qquad \forall j \in J, \forall t \in T$$

3.3.7. Logical status of commitment

The logical relationship between three binary variables corresponding to start-up status, shut-down status and the status of unit at each hour of the planning horizon is represented in constraint (33) while constraint (34) eliminates the conflicts between simultaneous start-up and shut-down by the unit.

$$y(j,t) - z(j,t) = I(j,t) - I(j,t-1) \qquad \forall j \in J, t \in T \tag{33}$$

$$y(j,t) + z(j,t) \le 1 \qquad \forall j \in J, t \in T \tag{34}$$

3.4. Thermal units' model

The linear model of thermal units is proposed through below formulations:

3.4.1. Fuel cost function considering POZ

Generally, fuel cost function of thermal units is presented by a quadratic function while the fuel cost function pertaining to thermal units is discrete as they are not able to operate in specific zone due to physical operating restriction. The equivalent piecewise linear model of the fuel cost function is depicted in Fig. 4 with *MPOZs*.

$$F(i,t) = \sum_{n=1}^{M+1} [\beta_n(i,t)F(p^u_{n-1}(i)) + b_n(i)\delta_n(i,t)] \quad \forall i \in I, \ \forall t \in T \tag{35}$$

$$P(i,t) = \sum_{n=1}^{M+1} [p^u_{n-1}(i)\beta_n(i,t) + \delta_n(i,t)] \quad \forall i \in I, \ \forall t \in T \tag{36}$$

$F(i,t)$ is piecewise linearized fuel cost function and binary variable $\beta_n(i,t)$ is equal to 1 if power block n for unit i of piecewise linearized fuel cost curve is selected. Cost of generation $p^u_{n-1}(i)$ is equal to $F(p^u_{n-1}(i))$. Slope and generation of power block n are used at second term. The power produced by thermal unit i at hour t is the sum of the "power length". Other constraints for linearization of fuel cost function can be stated as follows [40]:

The piecewise linearized form of the fuel cost function is denoted by $F(i,t)$ while $\beta_n(i,t)$ is a binary variable which is equal to 1 provided that the power block n for unit i of piecewise linearized fuel cost curve is selected. Moreover, generation cost denoted by $p^u_{n-1}(i)$ is equal to $F(p^u_{n-1}(i))$. The second term comprises slope and generation pertaining to power block n. the power generated by thermal unit i at time t is the sum of the "power length". Other constraints considered for linearizing the fuel cost function are stated as below [40]:

$$\delta_n(i,t) \ge 0 \qquad n = 1,2,\dots,M+1, \forall i \in I, \ \forall t \in T \tag{37}$$

$$\delta_n(i,t) \le [p^d_n(i) - p^u_{n-1}(i)]\beta_n(i,t) \qquad n = 1,2,\dots,M+1, \ \forall i \in I, \ \forall t \in T \tag{38}$$

$$\sum_{n=1}^{M+1} \beta_n(i,t) = I(i,t) \qquad \forall i \in I, \ \forall t \in T \tag{39}$$

$$\beta_n(i,t) \in \{0,1\} \quad n = 1,2,\dots,M+1, \forall i \in I, \ \forall t \in T \tag{40}$$

where, $p^u_0(i) = p_{\min}(i)$ and $p^d_{M+1}(i) = p_{\max}(i)$.

The power generated at each block should be positive and limited to its upper bound. The operation of the thermal units at only one of the operating zones is implied in constraint (39) e.g. if block 2 of the fuel cost curve is chosen for the thermal unit i ($\beta_2(i,t)$ is equal to 1), afterward $\delta_2(i,t)$ can be less or equal to the maximum "power length" of the second block $(p^d_2(i) - p^u_1(i))$ and other "other lengths" are set to zero. Consequently, thermal unit generation at this time would be $p^u_1(i)$ plus $\delta_2(i,t)$.

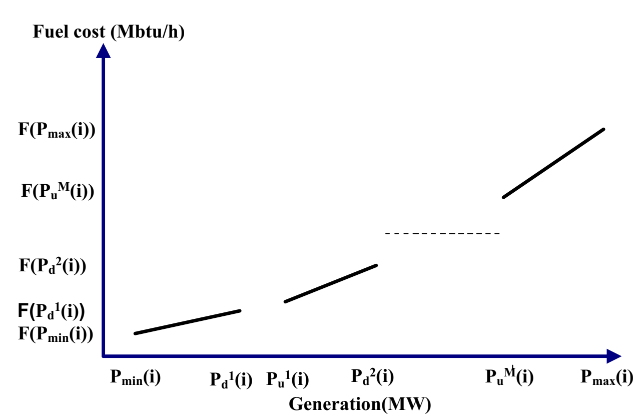

Fig. 4. Piecewise linear fuel cost curve with M prohibited operating zones.

3.4.2. Valve loading effects' cost

In thermal generating units with high installed capacity, there are multi-valve steam turbines. Once, the generated power is needed to be increased in such thermal units by ISO, the multi-valve turbines are opened in order; As a result, a ripple-like impact is produced in the heat rate curve of the thermal units [41]. The valve loading effects are taken into consideration in Refs. [41,42] as an absolute sinus function of the generated power while applying this sinus function to the model brings severe challenges in solving the realistic and large power systems due to high degree of non-convexity and also the state of being non-smooth. Thus, linear formulation is proposed in this paper to deal with the valve loading effects (Fig. 5).

$$C(i,t)=\frac{2e_i f_i}{\pi}\left\{\begin{array}{l}\sqrt{2}\sum\limits_{n=0}^{k_i}[\psi_{4n+1}(i,t)-\psi_{4n+4}(i,t)]\\ +(2-\sqrt{2})\sum\limits_{n=0}^{k_i}[\psi_{4n+2}(i,t)-\psi_{4n+3}(i,t)]\end{array}\right\}\quad \forall i\in I,\ \forall t\in T \tag{41}$$

$$p(i,t)=p_{\min}(i)I(i,t)+\sum_{n=0}^{k_i}\left[\begin{array}{l}\psi_{4n+1}(i,t)+\psi_{4n+2}(i,t)\\ +\psi_{4n+3}(i,t)+\psi_{4n+4}(i,t)\end{array}\right]\quad \forall i\in I,\ \forall t\in T \tag{42}$$

$$\frac{\pi}{4f_i}\chi_1(i,t)\le\psi_1(i,t)\le\frac{\pi}{4f_i}I(i,t)\qquad \forall i\in I,\forall t\in T \tag{43}$$

$$\frac{\pi}{4f_i}\chi_n(i,t)\le\psi_n(i,t)\le\frac{\pi}{4f_i}\chi_{n-1}(i,t)\quad \forall i\in I,\forall t\in T,n=2,3,\ldots,x_i \tag{44}$$

$$\chi_n(i,t)\in\{0,1\}\quad \forall i\in I,\forall t\in T,n=1,2,\ldots,x_i \tag{45}$$

where, $k_i=\text{floor}[f_i(p_{\max}(i)-p_{\min}(i)/\pi)]$ and $x_i=\text{floor}[4f_i(p_{\max}(i)-p_{\min}(i)/\pi)]$.

The valve loading effects' cost is denoted by $C(i,t)$ and the coefficients of valve point effects pertaining to the thermal unit i at time t are represented by f_i and e_i while $\psi_n(i,t)$ indicates the power generated by block n. The thermal power produced by thermal unit i at time t would be the sum of minimum output power once the unit is committed plus power generated in each block. The power generated in the first block is limited by constraint (43). This generated power must be smaller than or equal to $\pi/4f_i$ and greater than or equal to zero i.e. "power length" of each block. $I(i,t)$ ensures that if unit i is decommitted at time t, then the power produced at the first block is zero. Constraints (43) and (44) are used $\chi_n(i,t)$ to limit the power generated in each block introduce binary variable. Each time the power generated by the thermal unit i at time t has overstepped block n, this binary variable is equal to 1.

3.4.3. Generation thermal unit capacity limits

$$p_{\min}(i)I(i,t)\le p(i,t)\le\overline{p}(i,t)\quad \forall i\in I,\forall t\in T \tag{46}$$

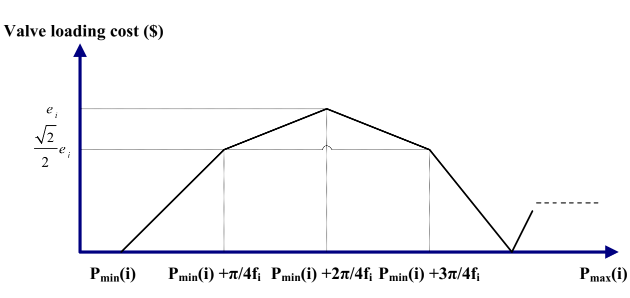

Fig. 5. Linear approximation of absolute sinus function of valve loading effect.

$$\overline{p}(i,t)\le p_{\max}(i)\{I(i,t)-z(i,t+1)\}+SD(i)Z(i,t+1)\quad \forall i\in I,\forall t\in T \tag{47}$$

$$p(i,t-1)-p(i,t)\le SD(i)Z(i,t)+RDL(p(i,t))\qquad \forall i\in I,\forall t\in T \tag{48}$$

$$p(i,t+1)-p(i,t)\le SU(i)y(i,t+1)+RUL(p(i,t))\qquad \forall i\in I,\forall t\in T \tag{49}$$

The power output limits of thermal units are given in constraint (46) implying that the generated power at time t should be less than the upper bound and greater than the minimum output power provided that the unit is committed. The upper bound of thermal units at any time of study is indicated in constraint (47) considers the status of thermal units. If the status of the unit is off at next hour, the generated power should be less than the shut-down limit. The shut-down ramp rate as well as Ramp-Down Limit (RDL) is represented in constraint (48). Constraint (49) includes the start-up ramp rate and Ramp-Up Limit (RUL). Furthermore, the dynamic ramp rate is considered in this paper instead of fixed rate to derive more precise model unlike majority of published papers.

3.4.4. Dynamic RDL and RUL

The ramp rate limits restrict the power generated between two successive operating periods. The generators respond to the hourly variations in the system demand through increasing or decreasing the produced power. The presented dynamic ramp rate is a function of the output power taking into consideration POZs (Fig. 6).

$$RDL(p(i,t))=\sum_{n=1}^{M+1}RDL_n(i)\beta_n(i,t)\quad \forall i\in I,\forall t\in T \tag{50}$$

$$RUL(p(i,t))=\sum_{n=1}^{M+1}RUL_n(i)\beta_n(i,t)\quad \forall i\in I,\forall t\in T \tag{51}$$

The dynamic RDL and RUL are represented in constraints (50) and (51), respectively while the selected operating zone is denoted by $\beta_n(i,t)$.

3.4.5. Time varying start-up cost function

The cold start-up cost can be represented by the exponential function of number of hours that a thermal unit is off. Ref. [7] uses linear form of varying start-up cost function.

3.4.6. Reserve services

Refs. [43,44] use operating services to support sudden events like outages of transmission lines and generators. Operating reserves include spinning and non-spinning reserves. Spinning reserve is defined as the unloaded units of synchronized generation being available for use in ten minutes while non-spinning reserve is defined as the unsynchronized generating units that are available for use in ten minutes. The formulations used in this paper for spinning and non-spinning reserve are the same as the ones proposed in Ref. [44].

3.4.7. Minimum up-time (MUT) and minimum down-time (MDT)

If a unit is turned on, it should not be turned off for at least several hours, as it is restricted by the MUT limitation. On the other hand, if a unit is turned off, it should not be turned on for at least several hours. In this regard, formulations presented in Refs. [7,39] are used in this paper.

3.4.8. Logical status of commitment

The formulation proposed in section 2.3.7 [7,39] is utilized here to eliminate the conflicts between start-up and shut-down status at the same time.

3.5. Network security

The transmission constraints are modeled as linear constraints on the basis of DC power flow model as [45].

4. Case study

The model is implemented on the modified IEEE 118-bus system as shown in Fig. 7 to verify the effectiveness of the proposed framework. This system comprises 54 thermal units (33 coal-fired units, 11 gas-fired units and 10 oil-fired units) as well as 8 hydro plants. The detailed data of this system can be found in Ref. [8] in which thermal units 5, 10, 11, 28, 36, 43, 44 and 45 have valve loading effects cost and thermal units 7, 10, 30, 34, 35 and 47 have POZs limitations. Thermal units 8, 9, 10, 11, 15, 16, 17, 18, 21, 22, 23, 24, 28, 29, 30, 31, 32, 33, 34, 35 and 36 can generate emission. The data pertaining to the demand and thermal units is available in Ref. [46]. The computer system employed in this paper to solve the MIP optimization of SCUC problem is a Pentium IV PC with 2.6 GHz clock speed and 2 GB RAM using solver CPLEX in the GAMS [47] environment.

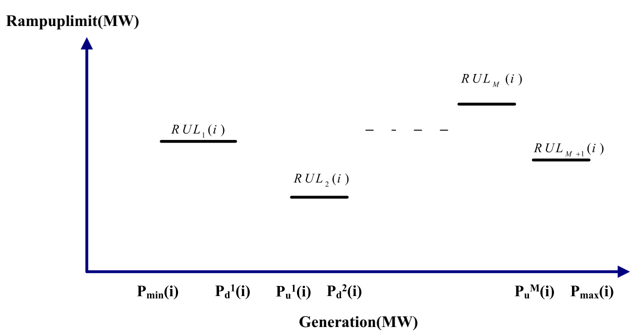

Fig. 6. Ramping up limit as a stepwise linear function of generation with *M* POZs.

4.1. Numerical results

In this paper, lexicographic optimization and hybrid augmented ε-constrain are used to generate the Pareto solutions of SCUC. The objective function F_1 i.e. cost minimization is taken into consideration as the main objective function in the ε-constraint technique. 49 grid points ($q_2=49$) is selected for F_2 (objective function $F^{emission}$) to derive Pareto optimal solutions from the MMP problem. The Pareto solutions are generated by solving the problem for 50 times ($q_2+1=50$) while all solutions are feasible [15,27,35]. Two cases are considered to study the presented SCUC where the first case only uses augmented ε-constraint technique without utilizing lexicographic optimization. The resulted payoff table (Φ_1) is represented as below:

$$\Phi_1 = \begin{bmatrix} 172,224.770 & 54,417.601 \\ 348,006.792 & 1908.816 \end{bmatrix}$$

The first column corresponds to the first objective function ($F_1=F^{COST}$) and the second column gives the results obtained for the objective function F_2 i.e. emission minimization while all the

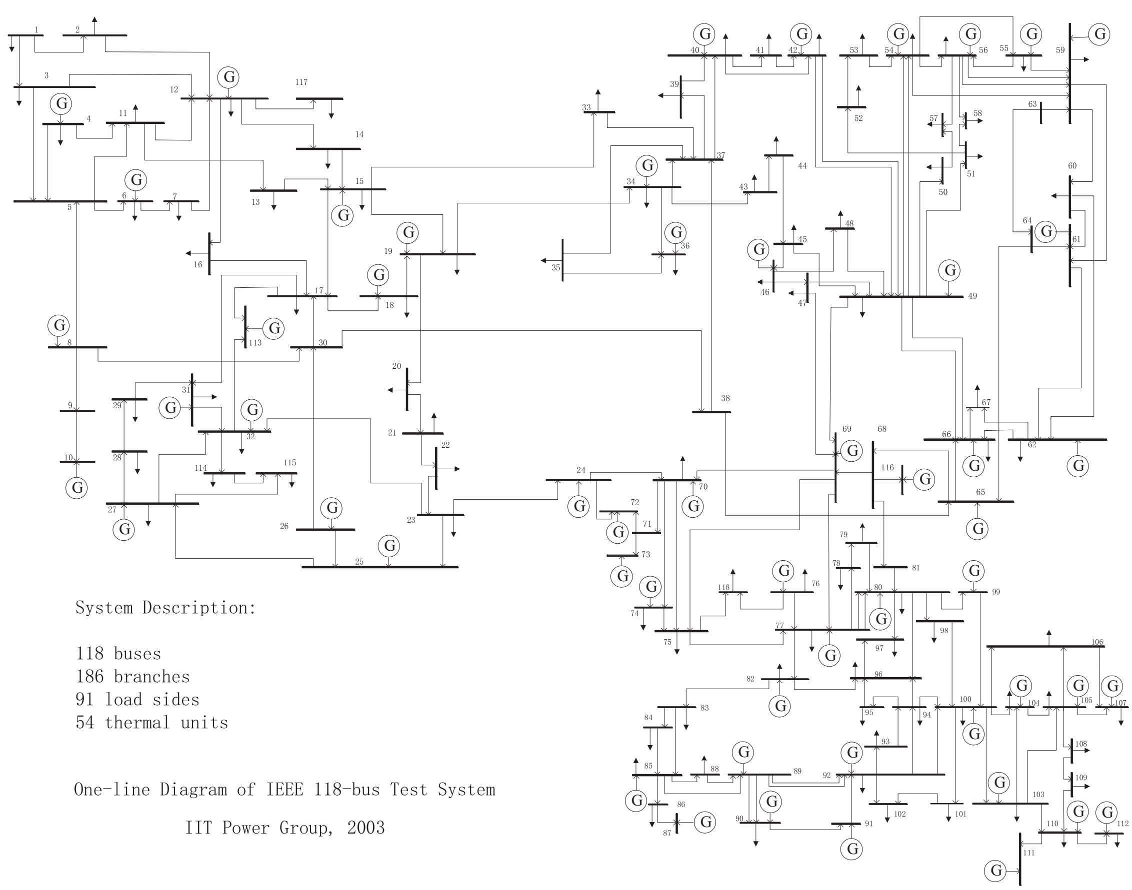

Fig. 7. Single-line diagram of 118-bus system.

obtained results are in terms of \$. Moreover, the main diagonal of the payoff table Φ_1 represents the results obtained from individual optimization of the objective functions (the *Utopia* points). As it can be observed, the single objective SCUC with F_1 as the objective function leads to the minimum cost but high amount of emission is generated in this case (54417.601 lbs). On the other hand, the results obtained for individual optimization of F_2 shows much less emission generation (1908.816 lbs) but with higher cost (348006.792 \$).

$$\Phi_2 = \begin{bmatrix} 172224.770 & 36642.31 \\ 232511.970 & 1908.816 \end{bmatrix}$$

As it can be seen in the values of the first row of payoff tables Φ_1 and Φ_2, the *Nadir* point pertaining to the second objective function F_2 is enhanced by 17775.291 (lbs) i.e. (54417.601–36642.31 = 1775.291 (lbs)). Therefore, narrower ranges are derived for all objective functions in Φ_2 compared to Φ_1, as the second row of the Φ_2 includes better results than those in Φ_1. This is because some inefficient Pareto solutions generated using ε-constraint technique, are discarded by lexicographic optimization and hybrid augmented ε-constraint method.

It is implied from payoff table Φ_2 that, cost can be decreased by ISO to 172224.770 (\$), if discards emission generation but results in emission equals to 36642.31 (lbs). On the other hand, if the second objective function is only taken into consideration i.e. $F^{emission}$, the amount of emission generation would decrease to 1908.816 (lbs) by ISO but leading to increase in cost to 232511.970 (\$). If, ISO have to consider the minimization of the emission generation in its multi-objective SCUC problem, the cost would increase by 60287.2 (\$) i.e. (232511.97–172224.77 = 60287.2 (\$)) in spite of substantial reduction in emission generation by 34733.494 (lbs) i.e. (36642.31–1908.816 = 34733.494 (lbs)). This state shows the conflicting nature of the two objective functions proposed in this paper.

A Fuzzy decision maker is utilized in this paper as Ref. [34] to select the most compromise solution among the Pareto solutions derived for the multi-objective SCUC problem. In the proposed Fuzzy decision maker, weighting factors corresponding to two objective functions are taken as the same. The total membership of all Pareto solutions is depicted in Fig. 8 while Pareto solution 40 is selected as the best one due to higher value of total membership obtained for this Pareto solution as 0.663. Table 1 represents the results obtained for the Pareto solution number 40 considering equal weighting factors. The total membership value in Table 1 shows the degree of optimality and equals to 0.663. The most preferred solution can be easily found by the DM by changing the weighting factors while ISO explicitly tends to minimize the cost rather than the emission. Therefore, by selecting the weighting factors as 2 and 1 for cost and emission, respectively, the obtained solutions in this state are represented in Table 2 while it is obvious that a Pareto solution with higher value of cost membership and

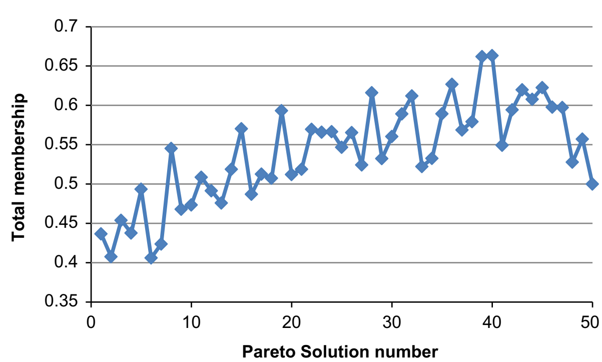

Fig. 8. Total membership value of Pareto solutions for equal weighting factor case.

Table 1
Optimum solution of SCUC with equal weighting factor.

Objective function	Weighting factor	Objective function value	Membership value
Cost	1	200520.56	0.772
Emission	1	8997.28	0.796
	Total membership of all objective functions		0.663

Table 2
Optimum solution of SCUC with different weighting factor.

Objective function	Weighting factor	Objective function value	Membership value
Cost	2	175381.22	0.948
Emission	1	31680.38	0.143
	Total membership of all objective functions		0.679

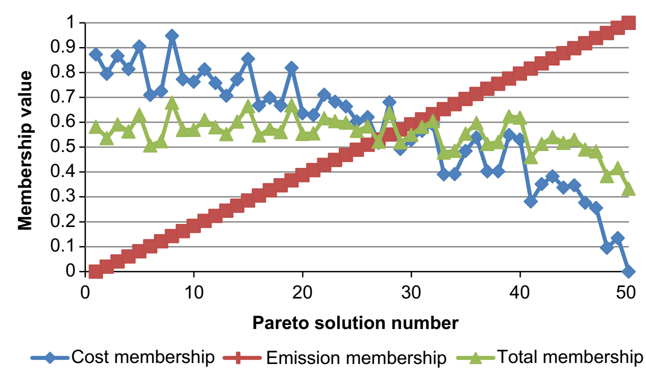

Fig. 9. Variation of objective functions and total membership value versus Pareto-optimal solutions for different weighting factor case.

Table 3
Optimization statistics for multi-objective SCUC problem.

No. of single constraints	No. of single variables	No. of discrete variables	No. of iteration	Solution time (s)
1521 666	1309 986	566 676	512 432	986

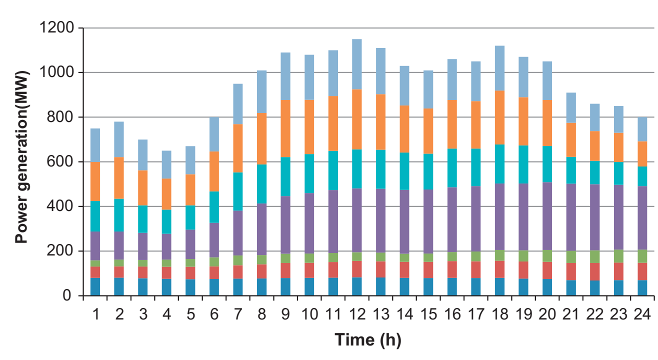

Fig. 10. The details of the best compromise solution with equal weighting factor.

lower value of emission membership will be searched. According to Table 2 and Fig. 9, a remarkable improvement in cost membership is observed as 0.772 in the case of equal weighting factors to 0.948 in the case of different weights. Table 2 represents the cost value as 175381.22 (\$) which is very close to its ideal value

Table 4
Results obtained from different methods.

Method	Ref. [20]			Ref. [29]			Ref. [30]			Ref. [31]			Proposed method		
	ELS	EES	CEES	ELS	EES	CEES	ELS	EES	CEES	ELS	EES	CEES	ELS	EES	CEES
Cost ($)	NR	NR	47,906	43,500	51,449	44,914	41,909	45,392	43,507	43,278	47,871	44,344	40,766.83	41,145.14	40,854.28
Emission (lbs)	NR	NR	26,234	21,092	18,257	19,615	30,724	17,659	18,183	17,984	17,019	17,408	18,278.57	15,666.61	16,180.20
Solution time (s)	NR	NR	4,582	72.96	72.74	74.97	NR	NR	NR	NR	NR	NR	1.78	1.12	15.68

NR = not reported.

i.e. 172224.77 but higher value of emission is obtained i.e. 31680.38 (lbs) while its membership value is low (0.143). The variation of objective functions and total membership value vs. Pareto-optimal solutions corresponding to different weighting factor case is shown in Fig. 9.

4.2. Discussion

An efficient multi-objective method is proposed in this paper that can be used by ISO for day-ahead scheduling of generation units even for large systems with lots of variables and constraints. The detailed optimization statistics for the multi-objective SCUC problem solved by lexicographic optimization and hybrid augmented ε-constraint method, is represented in Table 3. So far, there is no published paper implementing the SCUC problem for such a large system (IEEE 118-bus) comprising 54 thermal units as well as 8 hydro plants while two conflicting objective functions as cost and emission are optimized, simultaneously. In addition, many practical constraints, such as network security, valve loading effects, dynamic ramp rate limit and multi POZs of thermal units and multi performance curves for hydro units are considered in this paper. As a result, there is no published paper proposing such model and method for comparison purposes.

However, the proposed ε-constraint method has been implemented on a test case in Refs. [20,29–31] comprising 4 hydro units and 3 thermal units. The Economic Load Scheduling (ELS) presented in Refs. [29–31] only takes into consideration the economic issues. In addition, the Economic Emission Scheduling strategy is represented via EES intended to minimize the emission issues while CEES i.e. Combined Economic Emission Scheduling strategy optimizes two objective functions comprehensively by converting the original problem into a optimization problem with only one objective function employing a set of weights. The nonlinear formulation proposed in Refs. [20,29–31] is used to make a reasonable comparison with the results obtained in these works.

The optimal solution obtained from ε-constraint method considering equal weighing factors by DM is depicted in Fig. 10. The power generated by the first hydro unit and the first thermal unit for each hour is denoted by Ph1t and Ps1t, respectively. The ELS and EES can be calculated using the proposed method by optimizing economic load scheduling and economic emission scheduling, respectively. Note that, the payoff table is constructed by the results obtained from ELS and EES. The results of the proposed method are represented in Table 4 showing the superiority in the case of quantity for all cases compared to those obtained in Refs. [20,29–31]. For instance, the costs obtained using this approach is 7051.72 (47906–40854.28 = 7051.72), 4059.72, 2652.72 and 3489.72($) which are less than the ones obtained in Refs. [20,29–31]. Furthermore, the emission resulted via this method is less than the ones reported in Refs. [20,29–31] i.e. 10053.8, 3434.8, 2002.8 and 1227.8 (lbs). Also, the proposed method is better than other methods in the case of solution time. The optimization statistics for multi-objective SCUC problem on this test case are represented in Table 6. The results obtained from implementing the proposed approach demonstrate that the optimal daily generation scheduling of hydrothermal systems can be efficiently solved using lexicographic optimization and augmented ε-constraint method while the solution time is rationale.

5. Conclusion

The lexicographic optimization along with augmented ε-constraint technique are proposed in this paper and prosperously utilized to solve the multi-objective SCUC problem. Also, simulations have been done on the IEEE 188-bus system with 54 thermal units and 8 hydro plants to verify the effectiveness of the proposed method. The objective of ISO is to compromise the conflicting objectives of cost minimization and gaseous emissions minimization. The multi-objective SCUC problem is effectively solved employing the proposed method and Pareto optimal solutions are generated. Afterwards, a Fuzzy-based decision making procedure is implemented to select the most desired solution among Pareto optimal solutions. The obtained results using lexicographic optimization and augmented ε-constraint approach, in comparison with the ones obtained from an interactive fuzzy satisfying method [20], differential evolution method [29], quantum-behaved particle swarm optimization method [30] and cultural algorithm [31], confirms the capability of the proposed method both in the case of precision and execution time. The ongoing research work is to introduce security indices (overload index, voltage drop index and voltage stability margin) to the proposed problem.

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